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Research Article

Transformation in villages with digital financial inclusion: A case study in Karnataka villages

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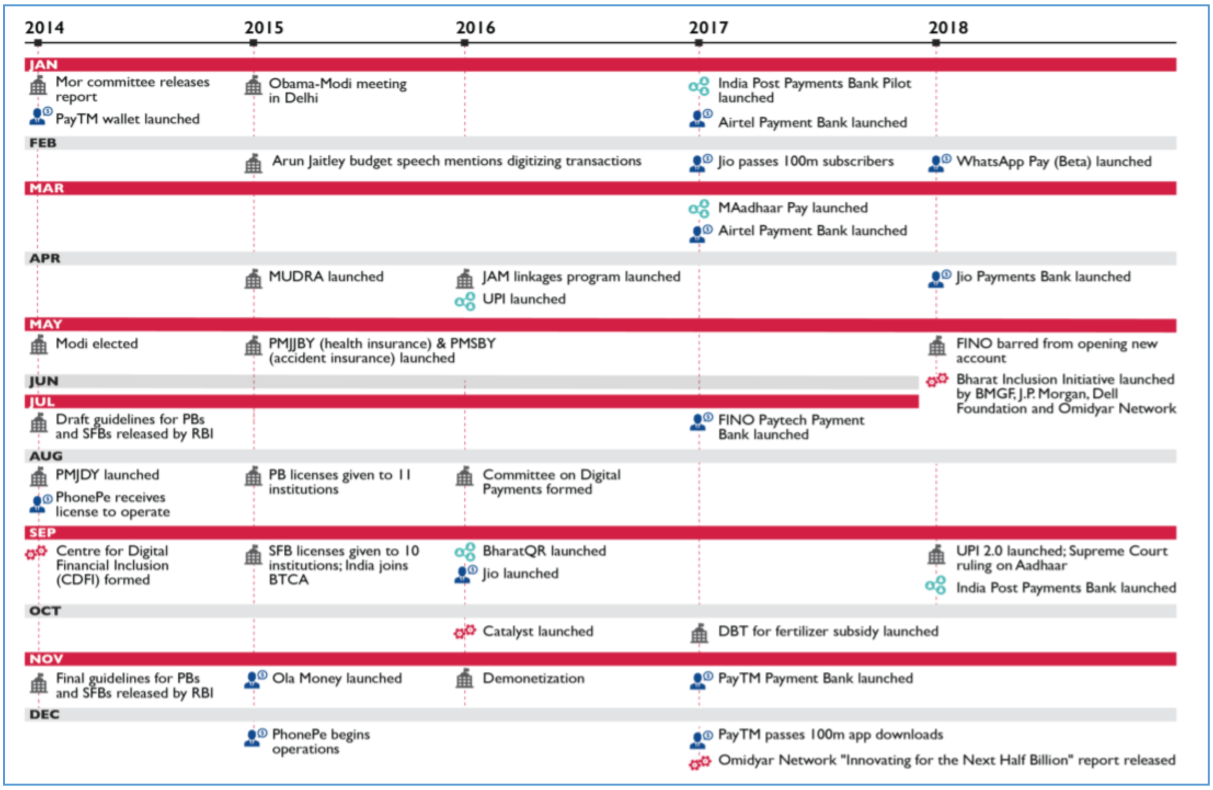
Abstract
India's soul lives in its towns and villages with almost 66% of its workforce in the villages. There are two kinds of the workforce in the villages – agricultural labour and service sector labourers. Agricultural labourers earn their livelihood on farming activities within the villages. Service sector labourers move to the nearest town for working in various services like construction, hotel, hospitality, etc. Over the last 10 years, the government of India has various digital financial inclusion schemes like Digital India, Direct benefit transfer, Rupay, UPI payments, etc. These schemes have increased the digital transactions in India as observed by many studies. Most of the existing studies on the impact of digital financial inclusion in India are based on macro economic factors. In this study, we analyse the transformations brought in Indian villages due to digital financial inclusion and propose a new Transformation Index(TI) based on both agricultural and service sector labourers. The validity of the transformation index is tested against 10 different rural areas of Karnataka. This scale is validated and reliability analysis of it is conducted through statistical tests.

Keywords: Financial inclusion, Digital India, Villages, Transformation Index

1. Introduction

India is a predominantly rural economy with it souls on villages and towns. According to World Bank (2019) estimates, 66% of India population live in villages. Most of these towns and villages were unbanked and did not have access to most of the financial services. Towards empowering them with financial services and improve their socio economic conditions, government of India has been launching various digital financial inclusion programmers over last 10 years. With greater financial inclusion, individuals who were previously financially excluded will be able to invest in education, save and launch businesses, and this contributes to poverty reduction and economic growth (Beck et al., 2007; Bruhn & Love, 2014). Financial inclusion also enables rural households to handle income shocks over unforeseen emergencies such as illness or loss of employment (Collins, Morduch, Rutherford, & Ruthven, 2009).

Government of India has launched its various financial inclusion initiatives under the flagship scheme named Digital India. Various initiatives under Digital India, like easy banking facilities for all, simplification of procedures relating to financial instruments, unique identification process of Aadhaar, simplification of tax procedures through the goods and services tax (GST), etc, have contributed significantly to the efforts of financial inclusion in the country. The Pradhan Mantri Jan-Dhan Yojana (shortened to PMJDY), a drive to provide all Indians with a bank account, was the cornerstone of this policy agenda. The key events in the financial inclusion activities by Government of India are summarized in Figure 1.



Jan Dhan–Aadhaar–Mobile (JAM) trinity has a positive impact on the banking sector and financial inclusion in the country. Jan Dhan accounts are linked to Aadhaar numbers of the individuals, which in turn is linked to the Direct Benefit Transfer (DBT) scheme. With the launch of JAM services, there has been a significant improvement in terms of targeted and accurate payments. The launch of Digital India has brought about a change in terms of payment facilities available to the stakeholders, especially from the underprivileged sections. KCC, general credit cards (GCC), and mobile banking facilities have been encouraging the poor to participate in the digital ecosystem. With the strengthening of the Unified Payment Interface (UPI) by RBI, digital payments have been made secure, compared to the past.

This paper work is a study on the impact of these digital financial inclusion programmes and transformation they have brought on rural citizens. The impact is analyzed on two different types of workforce in the villages – Agricultural and Service labourers. Agricultural labours earn their livelihood through farming and farming related activities like cattle rearing etc. Service labours move to nearby towns on daily basis for working in various industrial sectors like construction, hospitality, auto etc. This work analyse the impact of digital financial inclusion on these two types of workforce and propose a metric called Transformation Index (TI). This metric is an indicator of degree of transformation occurred in the individual due to digital financial inclusion. Following are the objectives of this work

- To design a new transformation index metric to measure the degree of transformation of rural workforce both agricultural and service sector labourers
- To test the reliability and validity of the transformation index for different rural areas.
- To study the impact of various JAM schemes in terms of transformation index.

2. Survey

A survey is conducted on existing works mainly to study the methods used in it for measuring the effectiveness of financial inclusion programmes.

Many questionnaire based studies on JAM schemes have been done. Prasad et al (2018) work on digital financial literacy among households in Udaipur city, Singhania et al (2018) work on adoption/deterrents of digitized financial services, Niranjan et al (2017) work on identification of hurdles in digital financial inclusion are some of the questionnaire based study. But in these works have not proposed any metric to measure the effectiveness of JAM schemes on individual personal level. Also these methods do not consider rural environment.

Many indexes are proposed for measuring the effectiveness of digital financial inclusion.
Sarma et (2008) used indicators of human development, income, literacy at personal level for measuring financial inclusion. At a population level, author used banking sector variables like NPA, interest rate and CAR to measure the financial inclusion. But the parameters considered at personal level are not specific for rural areas. Also authors have not proposed any means to remove the bias of other schemes apart from financial inclusion on these measures. The same author in this work in 2012, proposed a index of financial inclusion (IFI) to measure the effectiveness of financial inclusion. The index is a multi attribute Boolean metric with each attribute dependent on a macroeconomic factor. But both of the index are not suitable for measuring the transformation due to financial inclusion at personal level.
An asset based vulnerability model was proposed by Wang et al (2020). The effectiveness of the digital financial services is measured in terms of vulnerability risk estimated through asset based vulnerability model. Multiple macro and micro economic indicators are used to fit the vulnerability model. This model cannot be directly applied to Indian rural conditions due to difference of financial environment and unsuitability of many parameters considered in their vulnerability model. The effectiveness of digital financial inclusion was measured in terms of volume of mobile financial transaction by Hove et al (2019). Though the metric of volume of financial transaction is a good indicator for financial inclusion, authors have not quantified to measure the effectiveness and also did not propose any mechanism for establishing the baseline. A method for measuring the effectiveness of financial inclusion based on correlation to reduction in rural formal credit demand was proposed by Fu et al (2018). But in case of Indian rural area, most of credit demand is satisfied through informal sector and quantifying based on the level of formal credit demand will not work. A guideline for measuring the impact of financial inclusion based on poverty reduction and income inequality was proposed by Omar et al (2020). The metrics considered for generating the index for financial inclusion are per capita income, inflation, income equality, ratio of internet users etc. Index proposed in this work is based on macro factors and not suitable to measure effectiveness at rural area level and individual level. A financial inclusion index aggregating nine indicators of access, availability and usage was proposed by Park et al (2018). Poverty and income inequality were the two main parameters considered in this index. Two problems exist in use of this indicator – first it is suitable only for large population, second it is based on macro economic indicator. Thus we cannot use these indicators to measure the degree of transformation caused by digital financial inclusion at personal and a small population level for Indian rural areas.

2. Materials and methods/Methodology

2.1. Transformation Index
The transformation index proposed in this work for measuring the effectiveness of final inclusion for rural citizens is based on following dimensions

1. Online transactions of wages and spending
2. Saving, loan, informal credit involvement
3. Digital financial literacy

These dimension were selected on following important observations
Increase in volume of online transactions is a good indicator for financial inclusion as observed in the works of Hove et al (2019).
With increase in financial inclusion and bankability, there is an increased tendency for savings and using for needy times. Also the interest rates too motivate, citizens towards increasing the savings. A non-zero increasing balance in the account is a good indicator of financial inclusion. Bank loans are comparatively at cheaper interest in India compared to informal lenders. Thus a move towards bank loans and reduction in informal credits is a good indicator of financial inclusion as observed in the works of Fu et al (2018). Digital financial literacy is the awareness of - how to use the facilities of financial inclusion schemes for individual benefit. Person with sufficient digital financial literacy does not churn away from the formal banking system.
On each of three dimensions, questions are designed with score of 1-3 for each of questions. Say there are N questions, the answers are collected for each of the question. Say there are M samples, for each sample an N

element data vector is created with scores for each of the question. Score of each question is the feature for that dataset item. From the data of M sample, a dataset is created. This dataset is clustered using K-Means clustering algorithm. The number of clusters k is found using elbow method.
In the elbow method, the value of cost varies with different values of k. As k increases, the number of elements in the cluster reduces and also the average distortion. With lesser number of elements, the distance of cluster members to centroid is low. The point where the distortion declines the most is the elbow point as given in figure below

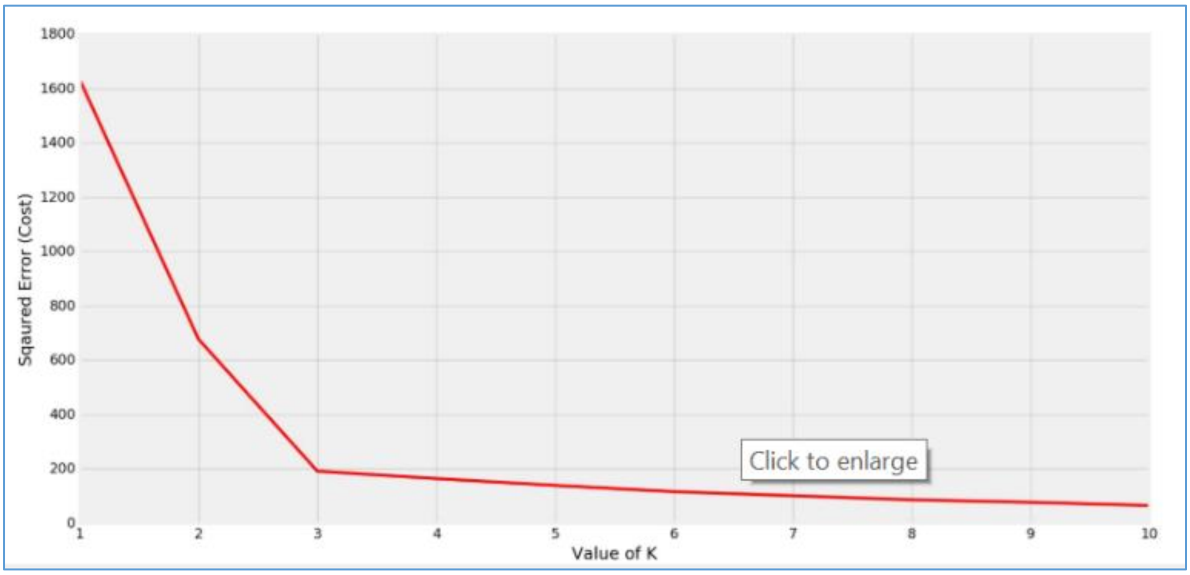


Figure 1 Finding K using elbow method

In the above figure, the cost is calculated in terms of square error (average of square of distance of members to centroid) and plotted against different values of k. Elbow is created at k=3, so the optimal value for k is decided as 3.

Fuzzy C Means clustering is done on the dataset with D for k as number of cluster. The cluster center after the fuzzy C means clustering is defined as

$$D = \{ D_{e,q} \text{ , } e = 1,2 \ldots k \text{ and } q = 1,2,3\}$$

Where $D_{e,q}$ is the qth coordinate of the eth cluster.
The closeness of the qth feature of the rth data f r,q with qth coordinate of eth cluster is defined using Gaussian function as

$$G(f_{r,q}, D_{e,q}, \sigma_{e,q}) = e^{\frac{(f_{r,q}-D_{e,q})^2}{\sigma_{e,p}{}^2}} \qquad (1)$$

Where

$$\sigma_{e,q} = \frac{1}{N_e}\sum_{r=1}^{N_e}(f_{r,q} - D_{e,q})^2$$

The closeness of features of rth data to the eth cluster is given as

$$\Psi_{r,e} = \prod_{q=1}^{P} G(f_{r,q}, D_{e,q}, \sigma_{e,q}) \qquad (2)$$

The output label for eth cluster is found from the linear regression of input features $f_{r,q}$ as

$$\Phi_{r,e} = W_{e,0} + \sum_{q=1}^{P} W_{e,q,f_{r,q}} \quad (3)$$

Where W is the regression coefficient of the eth cluster. Since each of the rth data has membership value to all P clusters, final label of that particular link is given by weighting the label of the link with its membership value as

$$\overline{N}(r) = \sum_{e=1}^{P} \Psi_{r,e}\Phi_{r,e} \quad (4)$$

The value of $\overline{N}(r)$ calculated above may have an error with respect to $N(r)$ from training. The total error is calculated as

$$E = \sum_{r=1}^{N} ||\overline{N}(r) - N(r)||^2 \quad (5)$$

The Gaussian parameters $D_{e,q}, \sigma_{e,q}$ and the regression coefficients $W_{e,p}$ are tuned to reduce the error defined above using gradient decent method.

$$D_{e,q}(t+1) = D_{e,q}(t) + \eta_C \frac{\partial E}{\partial D_{e,q}} \quad (6)$$

$$\sigma_{e,q}(t+1) = \sigma_{e,q}(t) + \eta_\sigma \frac{\partial E}{\partial \sigma_{e,q}} \quad (7)$$

$$W_{e,q}(t+1) = W_{e,q}(t) + \eta_W \frac{\partial E}{\partial W_{e,q}} \quad (8)$$

Where t is the iteration number and $\eta_C, \eta_\sigma, \eta_W$are the learning parameters. The iteration is stopped when error threshold is reached. From training the Fuzzy Gaussian membership functions are obtained for each class in terms of the features <PS, NS, and DS>.

Once the fuzzy membership function is generated for each cluster class, a TI score from 1 to 10 is assigned by the domain expert.

Once the score is available for N questions from an individual, the final TI score(TI_f) is calculated as

$$TI_f = \frac{\sum_{i=1}^{k} \Phi_{r,i} * \mathrm{TI}_i}{k} \quad (9)$$

Where $\Phi_{r,i}$ is the membership value for belonging to the cluster i and TI_i is score assigned for cluster by the domain expert.

The questions designed in each of the three dimensions are given in Appendix A.

2.2. Participants

The study is conducted across 2 districts with 5 villages in each district. A total of 200 respondents with 20 in each village participated in the study. The districts and villages (Table 1) used for study are in Karnataka state.

Table 1 Districts and villages studied

Districts	Villages	Number of Samples

Raichur	Raichur, Sindhanur, Manvi, Maski, Sirwar	100
Davangere	Davanagere, Harihar, Honnali, Channagiri and Jagaluru	100

The villagers with minimum secondary level education are considered for the study. The questionnaires were distributed to the samples and the responses are collected. The survey provided complete privacy to the subjects and did not collect any identity-related information from them.

2.3. Procedure

Questionnaires were distributed to the respondents and asked to respond to the questions in front of the research assistant. Since the data collection did not involve any vulnerable participants or funding source, the research study did not need any approval from any ethical review board. All the participants were well informed about the purpose of the study. Participants were not given any compensation for taking part in the study and there are no known risks in survey participation. The anonymity of participants is kept and no identifying information is collected from the participants. The questionnaires were administered in Kannada.
From the questionnaire responses of each sample, final TI score is calculated for each sample in each of 2 districts. From this a validation dataset of M samples is constructed.
Each of M samples has N feature corresponding to the score of each question and the output label as final TI score.

3. Results

Following tests were done to check for reliability of the questionnaire

1. Internal consistency
2. Test –Retest analysis

Internal consistency is checked by checking the homogeneity of 13 items in the questionnaire. The homogeneity is evaluated using Cronbach's alpha coefficient. For deciding the internal consistency, cronbach's coefficient of .7 or higher is decided as the threshold. Factor-based validity is verified by calculating the proportion of variance for all the scales and checking the number of items above the average. Test-Retest analysis was done by calculating the Pearson's correlation coefficient and intra-class coefficient for the responses from all the participants.
Test-Retest was done for all the response items for 13 questions in the questionnaire. The result of Pearson correlation coefficient and Cronbach's alpha coefficient is given below

Table 2 Reliability Analysis Result

Questions	**Items Cronbach's alpha coefficient**	**Item's Pearson correlation coefficient**
3	0.80	0.95
4	0.84	0.94
5	0.78	0.93
6	0.83	0.96
7	0.80	0.95
8	0.84	0.95
9	0.82	0.94
10	0.84	0.99
11	0.85	0.95
12	0.82	0.96
13	0.84	0.98

14	0.84	0.96
15	0.98	0,95

The cronbach's alpha coefficient is greater than threshold value of 0.7 and Test-retest reliability score is greater than 0.5. These two results indicate high internal consistency reliability of the questionnaire items.

After establishing the validity of the questionnaire, the reliability of the score is tested by multi-linear regression.

A multi-linear regression model is constructed for each of the two districts from the dataset of question answers vs final TI score calculated using Eq 9. Multiple linear regression is used to estimate the relationship between two or more independent variables and one dependent variable. In this work, the question responses are the independent variables and final TI score is the dependent variable.
The multi-linear regression model is built using SPSS tool. The model summary for Raichur and Davangere district is given below

District	**R**	**R square**	**Adjusted R square**	**Std error of estimate**
Raichur	0.760	0.5776	0.559	5.69
Davangere	0.761	0.5791	0.562	5.71

R is the multiple relation coefficient and it is indicator of measure of quality of prediction of dependent variable final TI score. For both districts of Raichur and Davangere, the value is more than 0.7. It indicates a good level of prediction and there is not much difference in the R value signifying the multi-linear regression model for final TI score is consistent.

ANOVA test is done to check if the overall regression model is good fit for the data and the result is given below

District	Sum of squares	df	Mean square	F	Sig.
Raichur	7273	99	73.46	32.393	0.000
Davangere	7281	99	73.54	32.413	0.000

Sig.(p) is less than 0.0005 inferring that the regression model is a good fit of the data and it is true for both the districts, thereby proving the consistency of the final TI metric.

4. Conclusion

This work proposed a new transformation index metric to measure the effectiveness of digital financial inclusion schemes. A simplified questionnaire of 13 items is designed to collect questionnaire responses from the village citizens in a simple 3 point scale. From the responses of each of the questions, the transformation index metric is calculated applying fuzzy c mean clustering algorithm. The validity of the metric is tested using various consistency test. The reliability of the metric is tested using multi-linear regression fit on data of two different villages and the result shows that almost the same result is achieved for multiple relation coefficient confirming the reliability of the metric. The goodness of fit is tested using ANOVA test and results proved higher fitness for final TI score.

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Ethical approval: Not applicable

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Appendix A: Questionnaire

Online transactions of wages and spending	
1. How frequently you use your online account for wages?	1. Do not use 2. Sometimes 3. Most of times
2. How frequently you use your online account for spending?	1. Do not use 2. Sometimes 3. Most of times

3. How frequently you maintain non zero balance in account?	1. Do not use 2. Sometimes 3. Most of times
4. How frequently you use your online account for transfer to friends and relatives ?	1. Do not use 2. Sometimes 3. Most of times
Saving, loan, informal credit involvement	
5. Has your savings increased due to access to digital banking?	1. Do not use 2. Sometimes 3. Most of times
6. Have you enquired digital loan facilities?	1. Do not use 2. Sometimes 3. Most of times
7. Is bank preferable compared to local lender?	1. No 2. Sometimes 3. Most of times
8 Do you use credit schemes in your account?	1. No 2. Sometimes 3. Most of times
9. Do you prefer banks in meeting your urgent financial needs?	1. No 2. Sometimes 3. Most of times
Digital financial literacy	
10. Are you aware of saving interest rates in your account?	1. No 2. Partly aware 3. Completely aware
11. Are you aware of all credit schemes in your account?	1. No 2. Partly aware 3. Completely aware
12. Are you aware of insurance schemes in your account?	1. No 2. Partly aware 3. Completely aware
13. Are you aware of aware of features in mobile payment app?	1. No 2. Partly aware 3. Completely aware